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Industry-Based Style Investing

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Abstract

Motivated by the style-investing model of Barberis and Shleifer (2003), we examine the industry-wide investment decisions of retail investors. We find that retail investor industry demand is highly correlated and strongly related to past industry returns. Moreover, industries heavily bought by retail investors over the past year significantly underperform industries heavily sold over the subsequent year. Similarly, stocks in industries heavily bought by retail investors underperform stocks in industries heavily sold, even after controlling for firm-level demand. Our results suggests that industry-wide categorization influences the investment decisions of retail investors and has a significant impact on asset prices.

Keywords: Retail Investors; Trading; Industry; Style Investing; Asset Pricing

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1. Introduction

There is growing evidence that investors often group stocks into categories or "styles" based on shared commonalities. For example, Barberis, Shleifer and Wurgler (2005) find that stocks added to the S&P 500 index begin to covary more with other members of the index, and Greenwood (2008) provides similar evidence for the Nikkei 225. Similarly, Green and Hwang (2009) document that stocks that undergo stock splits experience an increase in comovement with low-priced stocks and a decrease in comovement with high-priced stocks. These results are consistent with investors categorizing stocks based on index membership and price.[1]

Another potentially important category is industry. For example, Microsoft, Google, and Yahoo are often categorized as "technology stocks", while Merck, Pfizer, and Eli Lilly are often grouped together as "pharmaceutical stocks". Industry-wide categories are particularly important in the top-down investing approach, where investors first select promising industries before moving to stock selection. Industry analysis is also important for both buy-side and sell-side institutions. Buy-side institutions frequently offer sector oriented mutual funds such as "Vanguard Utilities" or "Fidelity Wireless Portfolio". Sell-side strategy analysts regularly issue industry-level forecasts and recommendations in their research reports. Similarly, firm-level analysts specialize by industry and often supplement firm-level recommendations with industry-wide recommendations (Kadan et al., 2012). Further, many financial phenomena, such as hot and cold IPO markets (Chemanur and He, 2011), mergers and acquisitions (Harford, 2005; Ahern and Harford, 2011), executive compensation (Lewellen, 2012), and stock market bubbles (e.g., the dotcom bubble) often have an industry-wide component.

If investors categorize stocks by industry membership, then their investment decisions

[1] Other papers that present evidence consistent with style-investing include Boyer (2011), Teo and Woo (2004), Kumar (2009), and Wahal and Yavuz (2013)).

will have an industry-wide component. This implies that industry-level reallocations should occur with greater intensity than reallocations across stocks grouped randomly. There are at least two reasons to expect that industry-level reallocations will be particularly strong amongst retail investors. First, retail investors tend to have more limited resources than institutional investors. Thus, retail investors seem more susceptible to simplifying complex investment decisions by categorizing stocks by industry. Indeed, processing information on 50 different industries is far less time consuming than processing information on thousands of different stocks. Second, prior research has found strong evidence that the trading of retail investors is systematically correlated (see e.g. Kumar and Lee (2006), and Barber, Odean, and Zhu (2009b).[2] Thus, if retail investors do categorize stocks by industry, it seems likely that the industry-wide investment decisions of individuals will aggregate into large industry-wide demand shocks.

In this paper, we explore three main questions about retail investor industry trading. First, is retail trading correlated at the industry level (i.e. do retail investors herd into and out of certain industries)? Second, how does retail investor industry demand impact both industry prices and stock prices? Third, to what extent is the poor performance of retail investor trading driven by their industry-wide investment decisions?

To answer these questions, we calculate the proportion of all trades in an industry that are buys (industry proportion bought) using the Trade and Quotes (TAQ) and Institute for the Study of Security Markets (ISSM) transaction data over the period of 1983-2000. We find that retail investor industry demand is highly persistent, consistent with retail investors following each other into and out of the same industries. For example, the cross-sectional correlation

[2] Prior research has also found that institutional investor trading is correlated; however the magnitude of retail investor herding is generally much larger than institutional herding. For example, Lakonishok, Shleifer, and Vishny (1992) and Grinblatt, Titman, and Wermers (1995) report herding measures of 2.7% for pension funds and 2.5% for mutual funds, respectively. In contrast, Barber, Odean, and Zhu (2009b) find that herding ranges from 6.8% for retail investors at a discount brokerage to 12.8% for retail investors at a full service brokerage.

between small trade proportion bought in week *t* and week *t+1* (*t+52*) averages over 60% (16%). Moreover, persistence in industry demand cannot be explained by retail investors following each out into and out of the same stock or stocks with similar size and book-to-market ratios. Consistent with the style investing model of Barberis and Shleifer (2003), we find that retail investors tend to chase industries that have performed well over the past two years. In fact, prior industry returns can forecast retail investor firm-level proportion bought, even after controlling for prior firm-level returns.

We next explore the asset pricing consequences of retail investor industry demand. We find that retail investor industry proportion bought over the prior week positively forecasts industry returns over the subsequent week. We also find that retail investor industry proportion bought over the prior quarter (6 months or year) negatively forecast industry returns over the subsequent quarter (6 months or year). A portfolio that went short the value-weighted quintile of industries most heavily bought over the prior quarter and went long the value-weighted quintile of industries most heavily sold would earn an average abnormal return of 41 basis points per month over the subsequent quarter. These results support the style investing model of Barberis and Shleifer (2003) and are inconsistent with rational explanations of correlated industry trading.

Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) find that retail investor firm-level demand also forecasts firm-level returns. To explore whether the asset pricing consequences of retail investor industry demand are distinct from firm-level demand, we perform double sorts on firm-level and industry proportion bought. Specifically, we first sort stocks into quintiles based on firm-level proportion bought and then within each quintile, sort stocks into industry proportion bought quintiles. Consistent with Barber, Odean, and Zhu (2009) and Hvidkjaer (2008), we find that stocks heavily bought by retail investors over the past 3 to 12 months significantly underperform stocks heavily sold by retail investors over the subsequent

3 to 12 months. More interestingly, we find that across all firm-level proportion bought quintiles, stocks in industries heavily bought by retail investors continue to significantly underperform stocks in industries heavily sold by retail investors. For example, amongst the quintile of stocks most heavily bought over the past 6 months, stocks in industries that were also heavily bought over the past 6 months earn abnormal returns of -28 bps per month, while stocks in industries that were heavily sold outperform by 20 bps, and the difference of 48 bps is highly significant. Our results suggest that industry-wide sentiment has an effect on asset prices that is distinct from firm-specific sentiment.

To better understand the extent to which the poor performance of retail investor trading is driven by industry-wide sentiment, we decompose retail investor performance into a firm-specific component and an industry-wide component. We find that industry selection is responsible for roughly 60% of the poor performance documented by Barber, Odean, and Zhu (2009). Moreover, after controlling for industry selection, we find that the stock picking ability of retail investors is typically not significantly different from zero. The results suggest that industry sentiment explains a significant portion of the poor performance of retail trades.

Lastly, we compare our findings of small trade industry demand with the results based on large trade ("institutional") industry demand. Consistent with prior work on institutional industry herding (e.g. Choi and Sias (2009) and Froot and Teo (2008)), we find statistically significant evidence of persistent industry demand by institutions. However, retail investor industry demand is roughly twice as persistent as institutional industry demand. Moreover, we find no significant relationship between institutional industry proportion bought and longer-horizon industry returns.

This paper contributes to the growing empirical literature on style investing. To our knowledge, this is the first paper that examines the industry-wide investment decisions of retail investors. Kumar (2009) finds that retail investors herd into similar size and book-to-market styles and finds some evidence of style-level momentum. We show that even after controlling for size and book-to-market, retail investors trading is correlated at the industry level. Moreover, we are able to document both style-level momentum at weekly horizons, and style-level reversals at quarterly to yearly horizons. Choi and Sias (2009) and Froot and Teo (2008) examine industry herding, but focus exclusively on institutional investors. We show that relative to institutions, retail investor industry demand is significantly more correlated and has a substantially different impact on industry prices.

We also contribute to the literature that explores the role of industries in understanding asset prices. While the corporate finance literature has long emphasized the importance of industries in understanding a variety of phenomenon (e.g., equity issuance, mergers and acquisitions, and CEO compensation), the role for industries in asset pricing has been more limited (Fama and French, 1997). One notable exception is Moskowitz and Grinblatt (1999) who find that industry momentum investment strategies are profitable even after controlling for firm-level momentum. Similarly, we document that retail investor industry demand forecasts stock returns even after controlling for retail investor firm-level demand. Our findings provide further evidence that industries can have an important conditional role on asset prices. In addition, our evidence suggests that much of the cross-sectional variation in sentiment across stocks can be attributed to industry-wide sentiment.

The remainder of this paper is organized as follows. Section 2 discusses the data and presents descriptive statistics. Section 3 examines whether retail investor trading is correlated at the industry level. Section 4 investigates the relationship between industry demand and subsequent industry and stock returns, and also decomposes the poor performance of retail investors into an industry component and firm component. Section 5 concludes.

2. Data

The data for this study come from several sources. We obtain data on returns, market capitalization, and industry classifications (SIC codes) from the Center for Research and Security Prices (CRSP). We obtain book value of equity form Compustat. We include all ordinary shares (CRSP share code 10 or 11) with adequate data. We assign each stock to one of 49 Fama and French (1997) industries.[3] Lastly, we obtain transaction data from the Institute for the Studies of Securities Market (ISSM) and the Trade and Quote database (TAQ). The ISSM dataset includes all transactions made on the NYSE and AMEX from 1983-1992 and covers NASDAQ stocks from 1987-1992. TAQ data includes all transactions from 1993 to present.

The data do not specify whether the executed trade was a buy or sell. We use the Lee and Ready (1991) algorithm to classify trades as either buyer or seller initiated. Specifically, if a trade is executed above (below) the quoted midpoint, the trade is classified as a buy (sell). If the trade is executed at the quoted midpoint, the executed trade price is compared to the preceding trade; the trade is considered a buy (sell) if the executed price was above (below) the last executed trade price. Thus all trades are classified as either a buy or a sell.

The data do not distinguish between trades made by retail investors and institutional investors. Instead, we use trade size as a proxy for individual and institutional trading. Following Barber, Odean, and Zhu (2009), trades less than \$5,000 (small trades) are used to proxy for retail investor trading. Trades greater than \$50,000 (large trades) are used to proxy for institutional investors.[4] Barber, Odean, and Zhu (2009) provide evidence that small trade order imbalance is positively correlated with order imbalance of retail investors at a large discount broker and a large retail full-service broker. Moreover, large trade order imbalance is negatively correlated with order imbalance from both the large discount and large retail broker, suggesting that trade size is a reasonable proxy for investor type. However, Hvidkjaer (2008)

[3] We use the updated industry definitions available on Ken French's website.
[4] Hereafter, we use the term "small trader" and "retail investor" synonymously. Similarly, we use the term "large trader" and "institutional investor' interchangeably.

finds that many of the patterns associated with small trades disappear after 2000, presumably because it became more common for institutions to break up large orders into smaller trades after the introduction of decimalization in 2001. Consequently, we limit our analysis to data from 1983-2000.

In each week (month or year), from January 1983 to December 2000, for each industry, we calculate the industry proportion bought amongst retail and institutional investors. We define industry proportion bought as the number of buyer initiated trades in a given industry divided by the number of total trades in that industry. Results are very similar if we value weight each trade by the dollar volume traded.

Table 1 provides the time-series mean of cross-sectional monthly descriptive statistics. Panel A presents industry statistics. The average industry includes 98 firms, with the minimum industry containing only 5 firms and the maximum industry containing over 500 firms. The largest industry represents, on average, 10.78% of the market portfolio, while the smallest industry account for 0.08% of the market portfolio. The largest stock in an industry accounts for roughly 30% of the average industry's market capitalization.

Panel B provides descriptive statistics on retail investor and institutional investor trading across industries. In the average industry, retail investors execute over 58,000 trades, although this ranges from 321,243 trades in the most heavily traded industries to 3,278 in the least heavily traded industries. Institutional investors execute roughly 48,000 trades in the average industry. Industry proportion bought exhibits substantial cross-sectional variation. Retail investors are net buyers 65% of the time in their most favored industries and only 37% of the time in their least favored industries. Institutional investor industry proportion bought ranges from 60% to 43%. The fact that retail investor industry proportion bought has a greater cross-sectional standard deviation than institutional investor industry proportion bought is consistent with our conjecture that industry demand is more correlated amongst retail investors.

One concern is that retail and institutional investor trading are simple complements. Since all non-institutional investors are retail investors, and since every trade is both a buy and a sell, it seems to follow that if retail investors are buying into an industry, institutions must be selling out of the same industry. To examine this, we calculate the correlation between retail investor and institutional investor industry proportion bought. We find that the time-series average of monthly cross-sectional correlations is -0.03. This indicates that small and large trade industry order imbalances are not simple complements.

There are at least two explanations for the relatively weak negative correlation between small and large trade industry proportion bought. First, our measure of small and large trade proportion bought only considers active trading through market orders. Thus passive traders who provide liquidity, either as market makers or though limit orders, are not included. This distinction is important, because a sizeable fraction of retail investor trading is done through limit orders.[5] We believe that active trades are a better measure of investor sentiment than limit orders, because whether a limit order is executed depends on the actions of others. For example, suppose retail investors have no strong belief about the technology sector and submit an equal amount of buy and sell limit orders. If institutional investors become bullish on the technology sector, then the sell limit orders of retail investors will be executed, while the buy limit orders will not. In this case, the heavy sell order imbalance of retail investors simply reflects the preferences of institutional investors.[6]

The second reason our results are not complementary is because our small trading measure is meant to capture the trading of small retail investors, rather than all non-institutional investors. For example, our small trading measure is probably not very representative of the trades of very wealthy individuals. These individuals make up a sizeable

[5] Linnainmaa (2010) finds that limit orders account for roughly 70% of all orders placed by retail investors.
[6] Consistent with this reasoning, Linnainmaa (2010) finds that the use of limit orders significantly alters inferences about individual's trading intentions and investment abilities.

portion of non-institutional trading. Wolff (2004) reports that the wealthiest 1% of households are responsible for over one-third of all US household ownership in stocks. Moreover, recent empirical evidence suggests that the trading behavior of these wealthy individuals is motivated by different considerations than the small retail traders who are the focus of this study. For example, Koirnoitis and Kumar (2013) finds that the trading behavior of retail investors with high cognitive ability (which they find is highly correlated with wealth) tends to be more motivated by information reasons, while the trading behavior of retail investors with low cognitive ability is more motivated by psychological biases.

3. Is Retail Investor Industry Demand Correlated?

In this section we examine whether the industry-wide trading of retail investors is systematically correlated. In sections 3.1 and 3.2 we examine the extent to which retail investor industry demand is correlated using the herding measures of Lakonishok, Shleifer, and Vishny (1992) and Sias (2004), respectively. In Section 3.3, we examine the extent to which industry demand is driven by past industry returns.

3.1 The Lakonishok, Shleifer, and Visny (1992) herding measure

We first examine whether retail investor demand is contemporaneously correlated. Each month we compute the proportion bought in each industry. We then calculate the Lakonishok, Shleifer, and Vishny (1992) herding measure (H_{it}). Let pb_{it} be equal to the proportion bought in industry *i* in month *t* and let E[pb_t] be the aggregate proportion bought (across all industries) during month *t.* The herding measure for industry *i* in month *t* is computed as follows:

$$H_{it} = \left| pb_{it} - E\left[pb_t \right] \right| - E\left[\left| pb_{it} - E\left[pb_t \right] \right| \right]$$

The first term measures the difference between the proportion bought in industry *i* and the average proportion bought across all industries. Since the difference is an absolute value, the first term will always be non-negative. The second term in this equation is the expected value of this herding measure under the null hypothesis of no herding.[7] In essence, this equation, examines whether the realized industry proportion bought is "fat-tailed" relative to the expected industry proportion bought under the null of no industry herding.

Each month we calculate this industry herding measure for both retail and institutional investors. We average the herding measure across all 49 industries and then take the time-series average. We find that the average industry herding measure amongst retail investors is 4.01%, while the average industry herding amongst institutional investors is 2.09%. Both measures are significantly greater than zero (p-value < .001). To get a sense of the economic importance of this effect, the 4.01% herding measure implies that if the average proportion bought was 50%, then in the average industry, 54.01% of retail trades would be on one side of the market (e.g., buying), while the remaining 45.99% of retail trades would be on the other side of the market (e.g., selling).

3.2 The Sias (2004) herding measure

An alternative measure of herding, proposed by Sias (2004), is to examine the cross-sectional correlation between the proportion bought in period t and period $t+1$. This measure allows us to examine the persistence of investors' industry-wide demand. Specifically, we examine the cross-sectional correlation between retail investor (institutional) industry proportion bought in week t and retail investor (institutional) industry proportion bought in week $t + x$, where x ranges from 1 week to 104 weeks. Figure 1 reports the time-series average of the cross-sectional correlations across all time periods. The correlation between retail investor industry demand this week and the prior week is over 60%. This correlation gradually declines to roughly 45% after four weeks, 34% after 12 weeks, 16%

[7] Since pb_{it} follows a binomial distribution, the expected value of this measure can be computed for any given average proportion bought (i.e. the probability of success) and the number of trades.

after 52 weeks, and 8% after 104 weeks. All estimates are significantly greater than zero.[8] Thus retail investor industry trading is not only contemporaneously correlated but also highly persistent. Moreover, across all horizons, the magnitude of the retail herding is typically two to three times the size of institutional herding.

One concern is that industry-level herding may simply be a manifestation of the firm-level herding documented by Barber, Odean, and Zhu (2009). To address this concern, we follow Choi and Sias (2009) and decompose the correlation between industry proportion bough in week *t* and week *t+1* into a firm-specific component and an industry-wide component. Specifically, we first compute a firm-level proportion bought for all stocks. We then calculate a weighted industry proportion bought by value-weighting (by market capitalization) the firm-level proportion bought across all stocks in the industry. Since the weighted industry proportion bought is a linear function of the proportion bought for each security in the industry, we can partition the total correlation into the correlation that is due to retail investors following each other into and out of the same stock, and the correlation that is due to retail investors following each other into and out of different stocks in the same industry. [9]

Panel A of Table 2 presents the results of the decomposition. The total correlation between retail investor industry proportion bough in week *t* and *t+1* is 63.8%. Roughly one-third of the total correlation can be attributed to correlated trading at the firm level (21.2/63.8), while the remaining two-thirds of the total correlation (42.6/63.8) is driven by retail investors following each other into and out of different stocks within the same industry. This indicates that industry herding is distinct from firm-level herding.

An additional concern is that industry herding may be due to the fact that stocks in the

[8] Standard errors are computed from the time-series average. We adjust for serial correlation using the New West (1987) approach.
[9] Additional details of the decomposition are available in section 3.4 (specifically equation 6) of Choi and Sias (2009).

same industries tend to have similar characteristics such as similar size and book-to-market ratios. For example, technology stocks tend to be growth oriented, while utility stocks tend to be value stocks. Several studies provide evidence that investors tend to categorize stocks based on size and book-to-market (see e.g., Teo and Woo (2004), Kumar (2009), and Wahal and Yavuz (2013)). Thus, it is worth examining whether industry herding persists after controlling for both firm-level herding and herding into stocks with similar size and book-to-market ratios.

To address this concern, we assign all stocks in the same industry to one of six size and book-to-market groups based on the Fama and French (1993) methodology. Then, following Choi and Sias (2009), we further decompose the total industry herding component (i.e. the 42.6%) into herding into stocks within the industry that are in the same size and book-to-market group versus herding into stocks in the same industry but in a different size and book-to-market group.[10] Panel B of Table 2 indicates that roughly 30% (12.9/42.8) of retail investor industry herding is driven by following investors into and out of stocks in the same size and book-to-market group, while the remaining 70% is driven by retail investors following each other into stocks in different size and book-to-market groups. Overall, our findings suggest that retail investor demand has an industry component that is distinct from firm-level demand or demand for stocks with certain size and book-to-market attributes.

3.3 Prior Returns and Retail Investor Demand

The previous results establish that retail investors have strong and persistent preferences for certain industries. The style investing model of Barberis and Shleifer (2003) posits that these preferences may be related to prior returns. Specifically, Barberis and Shliefer (2003) model an economy with two types of traders: fundamental traders and "switchers". Switchers move their wealth out of poorly performing styles and into styles that have

[10] Additional details of the decomposition are available in section 3.4 (specifically equation 7) of Choi and Sias (2009).

performed well. This suggests that retail investor industry proportion bought may be positively related to past industry returns.

To examine this prediction, each month (from January 1983 to December 2000) we sort industries into quintiles based on their equally-weighted performance over the past two years.[11] For each quintile, we compute the equally-weighted average retail investor industry proportion bought. Table 3 presents the time-series averages across the full sample period.[12] The table highlights that there is considerable cross-sectional variation in returns across industries. The bottom quintile of industries (i.e. the bottom ten industries) earn an annualized return of -4.89% over the past two years while industries in the top quintile earn an annualized return of 7.50%.

The table also reveals a monotonic relationship between past industry returns and retail investor demand. Specifically, retail investor proportion bought is 47.1% for industries in the bottom quintile. This number increases to 51.3% for the middle quintile, and 54.6% for the top quintile.[13] Consistent with retail investors focusing on industries with more extreme performance, the increases in proportion bought is more pronounced among the best and worst performing industries. For example, moving from the fourth quintile of past performance to the fifth quintile results in a 2.8% increase in proportion bought. In contrast, moving from the third to fourth quintile of past performance results in a much smaller increase of 0.6%. Similarly, moving from the second quintile to the first quintile generates a larger drop in proportion bought than moving from the third quintile to the second (2.2% vs. 1.5%).

Given retail investors' strong preference for industries that have performed well and

[11] Sorting based on value-weighted industry returns yields similar results.
[12] In untabulated analysis we have also computed standard errors based on the time-series standard deviation with a Newey-West (1987) adjustment for serial correlation. However, given the large sample size and long-time series, nearly all tests revealed statistically significant differences. Our emphasis in Table 3 thus focuses on economic significance.
[13] In untabulated analysis, we have also sorted industries into deciles. We continue to find a monotonic relationship between past returns and retail investor proportion bought. The proportion bought in the worst (best) decile is 47.0% (55.1%).

their aversion to poorly performing industries, it seems likely that much of the industry herding is driven by investors herding into (i.e. buying) winning industries and herding out of (i.e. selling) losing industries. To get a better sense for the magnitude of buying and selling-induced herding in winning and losing industries, we follow Wermers (1999) and compute a conditional herding measure. Specifically, the buy-herding measure (BHM) is simply the LSV herding measure conditional on retail investors having above average demand for the industry. In other words, $BHM_{i,t} = HM_{i,t} | p_{bi,t} > E[pb_{i,t}]$.[14] The sell-induced herding measure (SHM) is computed analogously. Each month we average $BMH_{i,t}$ (or $SMH_{i,t}$) across all industries in the quintile and then report the time-series average across all the month in the sample. Table 3 confirms that there is more buying-induced herding in top performing industries (5.99%) and more selling-induced herding in poorly performing industries (6.59%). In contrast, there is weaker evidence of selling-induced herding in better performing industries (2.27%) or buying-induced herding in poorly performing industries (2.85%).

We expect the relationship between past returns and small trader demand to be greatest in industries that are heavily owned by retail investors. To test this conjecture, we split industries into two groups based on the median breakpoint of retail investor industry ownership. We compute retail ownership as 1 – institutional ownership, where institutional ownership is computed from the 13F filings. We find a strong positive relationship between past industry returns and retail demand for both subsets of industries, but the effects are stronger for industries with higher levels of retail ownership. For example, the difference in proportion bought between the best performing industries and worst performing industries is 9.0% for industries with high retail ownership, compared to 5.1% for industries with low retail ownership.

[14] The adjustment factor used to compute $HM_{i,t}$ is recalculated conditioned on $pb_{i,t} > E[pb_{i,t}]$ again under the null hypothesis of no herding.

We next investigate the relationship between industry proportion bought and past industry returns in a regression framework. The regression allows us to easily explore how retail investor demand responds to past returns over different horizons. In addition, it allows us to control for past firm-level returns as well as past order imbalances. We begin by estimating the following cross-sectional regression:

$$\begin{aligned} Ind\_PB_{it} &= \alpha_0 + \beta_1 IndSize_{it} + \beta_2 IndBM_{it} + \beta_3 Ind\,\mathrm{Re}t_{it-1} + \beta_4 Ind\,\mathrm{Re}t_{it-3,t-2} + \beta_5 Ind\,\mathrm{Re}t_{it-6,t-4} + \beta_6 Ind\,\mathrm{Re}t_{it-12,t-7} \\ &+ \beta_7 Ind\,\mathrm{Re}t_{it-24,t-13} + \beta_8 IndPB_{it-1} + \beta_9 IndPB_{it-3,t-2} + \beta_{10} IndPB_{it-6,t-4} + \beta_{11} IndPB_{it-12,t-7} + \beta_{12} IndPB_{it-24,t-13} + \varepsilon_{it} \end{aligned}$$

The dependent variable is the industry proportion bought. The independent variables include IndSize and IndBM which are equal to the industry average size and the industry average book-to-market ratio (both in natural logs). We also include several measures of prior industry returns, ranging from the prior one month return to the return over the prior 13 to 24 months. In addition, we include lagged levels of industry proportion bought. To ease interpretation, we standardize all variables to have variance 1.

Panel A of Table 4 reports the time-series average of the cross-sectional results. Standard errors are computed using the Newey-West correction. The first column of Panel A reports the results prior to controlling for past industry demand. Industry proportion bought is insignificantly related to industry returns over the prior 3 months. This suggests that retail investors do not immediately withdraw assets from poorly performing styles and invest in recent winning styles. However, consistent with the findings in Table 3, industry proportion bought is positively related to prior industry returns over the past 4 to 6 months, 7 to 12 months, and 13 to 24 months. The impact of prior industry returns on industry proportion bought is both statistically and economically significant. For example, a one standard deviation increase in the industry return over the prior 13 to 24 months would increase the industry proportion bought by 4.3%.

We also examine whether prior industry returns can forecast industry proportion bought, after controlling for lagged industry proportion bought. The results of column 3 indicate that both prior industry return and prior industry proportion bought are significantly related to industry proportion bought. In untabulated analysis, we also examine whether institutional industry demand is related to past industry returns. We find some evidence that institutional investor industry demand is related to past one-month returns, but we find no evidence that institutional investors chase past returns over longer horizons.

A question of interest is whether style-level momentum trading is distinct from firm-level momentum trading. To address this question, we examine whether prior industry returns can forecast firm-level proportion bought after controlling for past firm-level returns. Thus, the dependent variable of this regression is the firm-level proportion bought and all the independent variables are firm-level variables with the exception of industry returns.

Panel B of Table 4 reports the time-series average of the monthly coefficients for this regression. Consistent with Hvidkjaer (2006), we find that retail investors tend to be firm-level contrarians over short horizons, but firm-level momentum traders over longer horizons. Moreover, after controlling for firm-level returns, industry returns now positively forecast firm-level proportion bought across all horizons. Thus over shorter horizons both firm-level and industry-level returns can forecast firm-level proportion bought but in opposite directions. The results suggest that prior industry performance and prior firm-level performance influences the investment decisions of retail investors in a fundamentally different way.

4. Industry Demand and the Cross-Section of Returns

The finding that retail investors buy winning industries and sell losing industries is consistent with the style investing model of Barberis and Shleifer (2003). The style investing model also argues that retail investor industry demand is motivated, at least in part, by investor sentiment. Consequently, the style investing model predicts that style-level sentiment pushes prices away from fundamentals in the short run leading to long-term reversals. Alternatively, it is possible that correlated trading by retail investors is driven by rational considerations, such as investors receiving correlated signals about fundamental information (see e.g. Froot, Sharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994)). If correlated trading by retail investors is driven by rational motives, then we would not expect retail investor industry demand to negatively forecast returns.

In section 4.1 we test these competing theories by examining whether retail investor industry demand negatively forecasts industry returns. In section 4.2, we investigate whether retail investor industry demand impacts firm-level returns even after controlling for firm-level demand.

4.1 *Industry Demand and Industry Returns*

We begin by examining the relationship between past industry proportion bought and subsequent industry returns. To capture the dynamic relationship between retail investor industry demand and subsequent returns, we consider a variety of formation periods and holding periods. The first strategy we consider is to sort on prior 1 week industry proportion bought and hold the portfolio for 1 week (1w-1w strategy). We also consider strategies that sort on prior 3 month industry proportion bough and hold the portfolio for 3 months (3m-3m strategy), as well as strategies that use holding periods and formation periods of 6 month (6m-6m) and 12 month (12m-12m).

For each strategy, we sort industries into quintiles based on the retail investor industry proportion bought over the formation period and then examine the return on the portfolio over the holding period. For example, for the 3m-3m strategy, from April 1983 to June 1983, portfolio 1 (5) would consist of the quintile of industries most heavily sold (bought) by retail investors from January 1983 to March 1983. For each portfolio, we first compute the value-weighted performance of each industry in the portfolio.[15] We then take the equally weighted average of each industry's return in that portfolio.[16] This gives us a time series of monthly returns starting in April of 1983 and ending in December of 2000.[17] All returns are reported as percent per month.

We begin by examining the 1w-1w strategy. Panel A of Table 5 reports the average monthly market-adjusted returns for each quintile. We find strong evidence that retail investor industry demand positively forecasts industry returns over the subsequent week. A portfolio that went long the industries most heavily bought by retail investors in the prior week and short the industries most heavily sold by retail investors, and rebalanced the portfolio each week, would earn a market-adjusted return of 72 basis points per month. In contrast, we find that institutional industry demand leads to short-term reversals, consistent with the short-term reversals documented by Jegadeesh (1990) and Lehman (1990).[18]

To see if the strong performance of retail investors is driven by retail investors loading on factors with good performance, we also compute five-factor alphas for each portfolio. We compute five-factor alphas using a time-series regression. The dependent variable is the monthly return on a given portfolio less the risk-free rate, and the independent variables represent factors related to market, firm size, book-to-market, firm-level momentum, and industry momentum. The first four factors are taken from Ken French's data library.[19] The fifth factor is included to control for the industry momentum effect document by Moskowtiz and Grinblatt (1999).[20] The five-factor alpha results indicate that a portfolio that went long the

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[15] Equally weighting each stock in the industry yields slightly stronger results.
[16] Value weighting by industry size yields very similar conclusions.
[17] In the case of the 1w-1w strategy, we obtain a time-series of daily returns which we compound into a time-series of monthly returns.
[18] In untabulated analysis, we find that both retail investor and institutional industry proportion bought is strongly related to contemporaneous returns, although the effect is roughly twice as large for institutions.
19 See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more details on the construction of these factors.
20 To construct the industry momentum factor, we use six value weighed portfolios formed on average industry size and prior 12 month industry returns. The portfolios, which are formed monthly, are the intersection of 2

industries most heavily bought by retail investors and short the industries most heavily sold by retail investors would earn a monthly alpha of 64 bps. This estimate remains highly significant and indicates that factor loadings cannot explain the positive relationship between retail investor industry demand and subsequent one week returns.

The short-term continuations following retail investor industry demand is consistent with either retail investors trading on value-relevant information or persistent retail investor demand pushing prices beyond fundamentals.[21] The former predicts that retail investor demand should be unrelated (or positively related) to longer-horizon returns while the latter suggest that retail investor industry demand should negatively forecast returns over longer horizons.

Panel B investigates the longer-horizon consequences of retail investor industry demand by sorting stocks into industries based on past 3 month retail investor industry demand. We find that the industries most heavily bought over the past 3 months underperform the industries most heavily sold by over 40 bps per month over the subsequent 3 months. Results are robust to using market-adjusted returns or five factor alphas and are statistically significant at a 1% level. Results are also qualitatively similar for the 6m-6m strategy and the 12m-12m strategy. Overall, the short-term continuations and long-term reversals following retail trading support the style investing model of Barberis and Shleifer (2003) and are inconsistent with rational motives for the industry-wide correlated trading of retail investors. In sharp contrast to our retail investor results, we find that institutional investor industry demand over the past 3 to 12 months is insignificantly positively related to future industry returns. The lack of reversal suggests that institutional investor industry demand is more motivated by rational reasons.

4.2 *Industry Demand and Firm Returns*

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portfolios formed on size and 3 portfolios formed on prior industry returns. Industry momentum is the average return on the two high prior return portfolios minus the average return of the two low prior return portfolios.

[21] A third explanation is that individual investors are compensated for providing liquidity to institutions that demand immediacy (see e.g. Kaniel, Saar, and Titman (2008)). However, since our measure of demand focuses exclusively on market orders, this explanation is unlikely.

Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) document that retail investor firm-level demand negatively forecasts firm returns over longer horizons. A natural question is whether retail investor industry demand also influences firm-level returns after controlling for retail investor firm-level demand. To explore this question, we first sort stocks into quintiles based on firm-level proportion bought. Within each firm-level proportion bought, we further sort stocks into quintiles based on industry proportion bought, resulting in 25 portfolios. As in Table 5, we consider 4 different formation periods (1w, 3m, 6m, and 12m) and 4 different holding periods (1w, 3m, 6m, and 12m). Within each portfolio we report the value-weighted five-factor alphas. Computing equal-weighted returns yields stronger results, and the results using market-adjusted returns are qualitatively similar.

Panel A of Table 6 presents the results for the 1w-1w strategy. Consistent with Barber, Odean, and Zhu (2009) we find that the stocks most heavily bought by retail investors over the prior week outperform the stocks most heavily sold by retail investors. More interestingly, we find that industry proportion bought also positively forecasts returns over the subsequent week. For example, amongst the stocks most heavily bought by retail investors, stocks in industries heavily sold by retail investors only outperform by 19 bps while stocks in industries heavily bought outperform by 80 bps, and the difference of 61 bps is highly significant.

Panels B through D indicate that industry demand also has predictability for longer horizon firm-level returns. For example, using the 3m-3m strategy, we find that amongst stocks heavily bought by retail investors, stocks in industries that were heavily sold by retail investors outperform stocks in industries that were heavily bought by roughly 54 bps per month. Similarly, amongst stocks that were heavily sold by retail investors, stocks in industries that were also heavily sold outperform stocks in industries that were heavily bought by roughly 44 bps. The results suggest that retail investor industry demand has explanatory power for the cross-section of stock returns above and beyond firm-level demand. One explanation for our findings is that firm-level demand consists of both rational and irrational demand. Conditioning on industry demand helps distinguish amongst the two. For example, if investors are bullish on Microsoft, their views are more likely to reflect rational considerations if they are bearish on other stocks in the industry (e.g., Apple and Dell). In contrast, a bullish view on Microsoft is more likely to reflect irrational optimism is they are also bullish on other stocks in the industry.

4.3 *The Relative Importance of Industry vs. Firm-Level Sentiment*

To better understand the relative importance of firm-level vs. industry-level demand in explaining the poor performance of retail trades, we decompose the total poor performance into firm and industry components. We begin by sorting stocks into quintiles based on firm-level proportion bought (as in Table 6). In other words, for each strategy we sort stocks based on retail investor firm-level proportion bought over the past *n* months (where *n* can equal 1 week, 3 months, 6 months, or 12 months) and then hold that portfolio for *n* months. The return on that portfolio is the value-weighted return of each stock in that portfolio. We then decompose the performance of this portfolio into industry performance and firm-level performance. Following Busse and Tong (2012), we compute industry performance by replacing each stock in the quintile with its value-weighted industry return. The industry return receives the same weight as the stock it represents in the portfolio. This measure is a proxy for the performance of retail investors that is due to their industry selection. The difference between their total performance and this industry performance is a measure of retail investor's performance due to their stock selection.

For example, suppose Microsoft made up 80% of quintile 1 and Goldman Sachs made up the remaining 20% of quintile 1. Suppose Microsoft earned 3%, Goldman Sachs earned 2%, the tech industry earned 1%, and the financial industry earned 4%. Under this scenario, quintile 1's total performance would be 2.8%, its industry return would be 1.6% and its firm return would be 1.2%.

Table 7 reports the results of this decomposition. Panel A reports the results for the 1w-

1w strategy. Consistent with Barber, Odean, and Zhu (2009) the total performance of retail investors is significantly positive over this horizon. A portfolio that went long the stocks most heavily bought by retail investors and short the stocks most heavily sold by retail investors would earn an average monthly five-factor alpha of 79 bps. The decomposition indicates that the industry selection is responsible for roughly 43 bps (54%), while the stock selection is responsible for 37 bps (46%). Both the industry component and stock level component contribute significantly to the short-term predictability.

Consistent with both Hvidkjaer (2008) and Barber, Odean, and Zhu (2009), Panels B, C, and D document a negative relationship between retail investor firm-level proportion bought over the prior quarter, six months, or a year, and subsequent firm-level returns. For example, Panel C indicates that a portfolio that went long the stocks most heavily bought by retail investors and short the stocks most heavily sold by retail investors over the prior 6 months, would earn an average monthly five-factor alpha of -54 bps over the subsequent six months. The decomposition indicates that roughly 63% (34 bps) of total underperformance is due to retail investors' industry-wide selection, while 37% (20 bps) is due to their firm-level selection. Moreover, the industry component remains reliably different from zero, indicating that the industry selection of retail investors contributes significantly to their overall poor performance. In contrast, the firm-level component is no longer significantly different from zero. More generally, across the 6 specifications in Panels B through D, the industry component is statistically significant at the 10% level in all 6 cases, while the firm-level component is significant at the 10% level in only one case.

One concern is that using value-weighted returns results in a mechanical relationship between industry returns and portfolio returns. For example, if a portfolio contains one very large firms and a number of small firms, the large firm is likely very influential in determining both the portfolio return and its corresponding industry return. To address this concern, in untabulated analysis, we repeat the analysis using equal weighted returns for both the return on the portfolio and the return on the corresponding industry. The results are qualitatively similar. For example, for the 6m-6m strategy, the five factor alpha for the total portfolio is -59 bps, of which roughly 61% (36 bps) is driven by the industry component.

5. Conclusion

This paper examines the industry-wide investment decisions of retail investors. We find that the industry-wide trading behavior of retail investors is consistent with the style investing model of Barberis and Shleifer (2003). Specifically, we find that retail investor trading is highly correlated at the industry level and is strongly related to past industry returns. Further, retail investor industry demand positively forecasts industry returns over the subsequent week, but negatively forecasts industry returns over the subsequent 3 months to a year. Thus, retail investors appear to behave very much like the "style switchers" described in Barberis and Shleifer (2003). Specifically, they chase industries that have done well in the past, pushing prices away from fundamentals.

In addition, we find that retail investor industry demand can forecast firm-level stock returns even after controlling for firm-level demand. This suggests that conditioning on both firm-level and industry-wide retail demand can provide a more complete picture of firm-level sentiment Further, our industry decomposition reveals that roughly 60% of the poor performance of retail trades is driven by the poor industry selection of retail investors. Moreover, this industry component remains significantly negative, while the firm-specific component is generally not reliably different from zero. This finding highlights the importance of retail investors' industry-wide investment decisions in explaining both asset prices and their trading performance.

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Table 1: Descriptive Statistics

Each month, from January 1983 to December 2000, we classify stocks into one of the Fama and French (1997) 49 industries. Panel A reports the time-series average of the cross-sectional descriptive statistics for the number of firms in each industry, the percentage of total market capitalization accounting for by each industry, and the fraction of industry capitalization accounted for the by the largest firm in the industry. Panel B reports the time-series average of the cross-sectional descriptive statistics for the number of small and large trades made in each industry, the proportion bought by small and large traders in each industry, and the percentage of total small and large trade industry trading accounted for by the largest firm in the industry.

	Mean	Median	Minimum	Maximum	Std Dev
Panel A: Industry Statistics					
No. of firms in industry	98	61	5	526	83
Industry capitalization/Market capitalization	2.04%	1.32%	0.08%	10.78%	2.17%
Largest firm in industry/Industry capitalization	30.56%	23.21%	4.98%	78.23%	9.34%
Panel B: Industry Trading Statistics					
No. of small trades in an industry	58,456	51,327	3,278	321,243	48,239
No. of large trades in an industry	47,987	42,340	2,861	265,397	37,309
Small trades proportion bought	51.06%	51.02%	36.55%	64.61%	3.03%
Large trades proportion bought	52.72%	52.89%	42.97%	59.89%	2.25%

Table 2: Decomposing Correlated Trading at the Industry Level

Each week from January 4, 1983 to December 27, 2000 we compute retail investor industry proportion bought. The *Total* column reports the cross-sectional correlation between industry proportion bought in week *t* and week *t+1*. In Panel A, we decompose this total correlation (*Total)* into the correlation due to retail investor following each other into and out of the same stock (*Same stock)* and the correlation due to following each other into different stocks in the same industry (*Different stocks in same industry).* Details on the decomposition can be found in Choi and Sias (2009) equation 6. In Panel B, we further decompose retail investors following each other into and out of different stocks in the same industry into two components: following each other into and out stocks in the same size and book-to-market group (*Same Size-BM group)* and following each other into and out stocks in different size and book-to-market groups (*Different Size-BM group).* Further details on the decomposition can be found in Choi and Sias (2009) equation 7. We report the time-series average of the weekly coefficient estimates. We compute standard errors using the Newey-West (1987) approach. T-statistics are reported in parentheses.

Panel A: Persistence in Industry Demand: Firms vs. Industries

Same stock	*Different stocks in same industry*	*Total*
0.212	0.426	0.638
(5.43)	(7.45)	(9.23)

Panel B: Persistence in Industry Demand: Same Size-BM groups vs. Different Size-B/M groups

Same Size-BM group	*Different Size-BM group*	*Different stocks in same industry*
0.129	0.297	0.426
(4.70)	(6.71)	(7.45)

Table 3: Retail Investor Demand and Prior Industry Returns – *Univariate Sorts*

Each month, from January 1983 to December 2000, we sort industries into quintiles based on their prior two year return. *Past Return* reports the average annualized prior two year return across all industries in the quintile. *Proportion Bought* captures the fraction of total small (i.e. retail) trades that were purchases. Buy Herding (BHM) is the LSV herding measure conditional on retail investor having above average demand for the industry. Sell Herding (SHM) is the LSV herding measure conditional on retail investor having below average demand for the industry. The final two columns report the proportion bought for the subset of industry with high (above the median) and low (below the median) retail ownership. Each month, all estimates are based on the equally-weighted averages across all industries in the quintile. The table report the time-series average across all the moths in the sample.

	All Stocks				Industries with High Retail Ownership	Industries with Low Retail Ownership
Quintile	Past Return	Proportion Bought	Buy Herding	Sell Herding	Proportion Bought	Proportion Bought
1 (Worst Ind. Return)	-4.89%	0.477	2.85%	6.59%	0.471	0.481
2	-0.77%	0.498	3.60%	4.69%	0.506	0.494
3	1.23%	0.513	4.24%	3.90%	0.514	0.511
4	3.29%	0.519	4.72%	3.55%	0.527	0.514
5 (Best Ind. Return)	7.50%	0.546	5.99%	2.27%	0.560	0.532

Table 4: Retail Investor Demand and Prior Industry Returns – *Regressions*

This table presents the results from industry-level (Panel A) and firm-level (Panel B) Fama-Macbeth regressions estimated monthly from January 1983 to December 2000. In Panel A, retail investor *industry proportion bought* is regressed on lagged industry returns, lagged retail investor industry proportion bought, industry average values of LN (Size) and industry average values of LN (BM). In Panel B, retail investor *firm-level proportion bought* is regressed on lagged industry returns, lagged retail investor firm proportion bought, lagged firm returns, firm LN (Size) and firm LN (BM). All independent variables are standardized to have variance 1. Time-series average values of the monthly regression coefficients are reported below. Standard errors are adjusted using the Newey-West (1987) correction. T-statistics are reported in parentheses.

Panel A: Retail Investor Industry Proportion Bought

	Coefficient	t-statistic	Coefficient	t-statistic
LN (Size)	-0.001	(-0.03)	0.001	(0.15)
LN (BM)	-0.022	(-5.32)	-0.020	(-4.97)
Ind_Ret_{t-1}	-0.012	(-1.30)	-0.008	(-0.96)
$Ind\_Ret_{t-3,t-2}$	-0.018	(-1.52)	0.005	(0.41)
$Ind\_Ret_{t-6,t-4}$	0.026	(3.43)	0.024	(2.65)
$Ind\_Ret_{t-12,t-7}$	0.035	(5.27)	0.032	(5.16)
$Ind\_Ret_{t-24,t-13}$	0.043	(7.27)	0.035	(6.85)
Ind_PB_{t-1}			0.293	(3.68)
$Ind\_PB_{t-3,t-2}$			0.188	(5.39)
$Ind\_PB_{t-6,t-4}$			0.329	(4.42)
$Ind\_PB_{t-12,t-7}$			0.218	(5.29)
$Ind\_PB_{t-24,t-13}$			0.089	(2.50)
Adjusted R^2	0.24		0.33	

Panel B: Retail Investor Firm Proportion Bought

	Coefficient	t-statistic	Coefficient	t-statistic
LN (Size)	0.005	(4.56)	0.004	(4.87)
LN (BM)	-0.013	(-5.56)	-0.010	(-5.64)
Ret_{t-1}	-0.057	(-10.36)	-0.051	(-8.35)
$Ret_{t-3,t-2}$	-0.042	(-7.47)	-0.038	(-7.59)
$Ret_{t-6,t-4}$	-0.013	(-0.13)	0.009	(1.32)
$Ret_{t-12,t-7}$	0.058	(9.75)	0.054	(9.33)
$Ret_{t-24,t-13}$	0.064	(11.24)	0.051	(9.93)
Ind_Ret_{t-1}	0.032	(3.30)	0.024	(2.98)
$Ind\_Ret_{t-3,t-2}$	0.031	(2.90)	0.027	(2.35)
$Ind\_Ret_{t-6,t-4}$	0.026	(2.54)	0.024	(2.43)
$Ind\_Ret_{t-12,t-7}$	0.038	(3.20)	0.029	(3.45)
$Ind\_Ret_{t-24,t-13}$	0.043	(4.20)	0.045	(4.36)
PB_{t-1}			0.231	(7.54)
$PB_{t-3,t-2}$			0.164	(7.01)
$PB_{t-6,t-4}$			0.087	(5.43)
$PB_{t-12,t-7}$			0.056	(4.35)
$PB_{t-24,t-13}$			0.030	(2.53)
Adjusted R^2	0.10		0.15	

Table 5: Industry Returns on Portfolios Sorted on Past Industry Proportion Bought

From January 4, 1983 to December 27 2000, portfolios are formed on prior retail investor (institutional) industry proportion bought over the past week (Panel A), quarter (Panel B), six months (Panel C) or year (Panel D). The industries most heavily sold (bought) are placed in portfolio 1 (5). We then examine the average return over the subsequent week (Panel A), quarter (Panel B), six months (Panel C) or year (Panel D). For each industry, we compute a value-weighted return, expressed in percent per month. The portfolio return is the equally-weighted average return across all the industries in the portfolio. Market-adjusted returns are the return on the portfolio less the value-weighted market return. Five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. The difference in return between quintile 5 and 1 is reported along with t-statistics in parentheses.

Panel A: 1 Week - 1 Week

	Market-Adjusted Return (%)			Five-Factor Alphas (%)		
Portfolio	Retail	Institutions	Difference	Retail	Institutions	Difference
1 (sold)	-0.286	0.423	-0.709	-0.147	0.328	-0.475
2	-0.181	0.389	-0.570	-0.253	0.349	-0.602
3	0.323	-0.290	0.613	0.195	-0.092	0.287
4	0.121	-0.212	0.333	0.102	-0.232	0.334
5 (bought)	0.438	-0.129	0.567	0.495	-0.121	0.616
B-S (5-1)	0.724	-0.552	1.276	0.642	-0.449	1.091
	(5.30)	(-5.04)	(6.89)	(4.29)	(-3.42)	(5.73)

Panel B: 3 Months - 3 Months

	Market-Adjusted Return (%)			Five-Factor Alphas (%)		
Portfolio	Retail	Institution	Difference	Retail	Institution	Difference
1 (sold)	0.375	-0.056	0.431	0.324	-0.017	0.341
2	0.282	0.249	0.033	0.162	0.148	0.014
3	0.102	0.189	-0.087	0.210	0.269	-0.059
4	0.023	0.179	-0.156	0.002	0.139	-0.137
5 (bought)	-0.101	0.107	-0.208	-0.090	0.093	-0.183
B-S (5-1)	-0.476	0.163	-0.639	-0.414	0.110	-0.524
	(-3.46)	(1.30)	(-4.36)	(-3.19)	(1.03)	(-3.79)

Panel C: 6 Months - 6 Months

	Market-Adjusted Return (%)			Five-Factor Alphas (%)		
Portfolio	Retail	Institutions	Difference	Retail	Institutions	Difference
1 (sold)	0.249	-0.021	0.27	0.245	-0.005	0.260
2	0.299	0.290	0.009	0.202	0.125	0.077
3	0.19	0.186	0.004	0.174	0.302	-0.128
4	0.100	0.193	-0.093	0.118	0.175	-0.057
5 (bought)	-0.162	0.045	-0.207	-0.142	0.015	-0.157
B-S (5-1)	-0.411	0.066	-0.477	-0.387	0.02	-0.407
	(-2.59)	(0.59)	(-2.49)	(-2.31)	(0.18)	(-24.70)

Panel A: 12 Months - 12 Months

	Market-Adjusted Return (%)			Five-Factor Alphas (%)		
Portfolio	Retail	Institutions	Difference	Retail	Institutions	Difference
1 (sold)	0.342	-0.032	0.374	0.274	-0.020	0.314
2	0.103	0.321	-0.218	0.135	0.359	-0.224
3	0.217	0.219	-0.002	0.263	0.242	0.021
4	0.066	0.142	-0.076	0.102	0.152	-0.050
5 (bought)	-0.043	0.082	-0.125	-0.070	-0.010	-0.060
B-S (5-1)	-0.385	0.114	-0.499	-0.344	0.010	-0.354
	(-2.22)	(0.97)	(-2.75)	(-2.12)	(0.45)	(-2.00)

Table 6: Portfolio Double Sorts on Firm and Industry Demand

This table examines the impact on past firm-level and industry-wide proportion bought on subsequent *firm* returns. From January 4, 1983 to December 27 2000, portfolios are formed on prior retail investor firm-level proportion bought over the past week (Panel A), quarter (Panel B), six months (Panel C) or year (Panel D). The firms most heavily sold (bought) are placed in portfolio 1 (5). Within each firm-level proportion bought quintile, we further sort stocks into quintiles past on the past industry proportion bought over the same formation period. We then examine the value-weighted return over the subsequent week (Panel A), quarter (Panel B), six months (Panel C) or year (Panel D) for each portfolio. Returns are five-factor alphas and are expressed as percent per month. The five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. For each firm proportion bought quintile, the difference in return between quintile 5 (stocks in industries heavily bought) and 1 (stocks in industries heavily sold) is reported along with t-statistics in parentheses.

Panel A: 1 Week - 1 Week

	Industry Proportion Bought				
Firm Proportion Bought	1 (Sell)	2-4	5 (Buy)	Q5 -Q1	t-statistic
1 (Sell)	-0.404	-0.264	-0.103	0.301	(2.05)
2-4	-0.103	0.005	0.281	0.384	(2.56)
5 (Buy)	0.185	0.478	0.798	0.613	(4.01)

Panel B: 3 Months - 3 Months

	Industry Proportion Bought				
Firm Proportion Bought	1 (Sell)	2-4	5 (Buy)	Q5 -Q1	t-statistic
1 (Sell)	0.502	0.353	0.064	-0.438	(-3.21)
2-4	0.352	0.008	-0.081	-0.433	(-3.37)
5 (Buy)	0.307	-0.104	-0.234	-0.541	(-4.97)

Panel C: 6 Months - 6 Months

	Industry Proportion Bought				
Firm Proportion Bought	1 (Sell)	2-4	5 (Buy)	Q5 -Q1	t-statistic
1 (Sell)	0.449	0.265	0.105	-0.344	(-2.30)
2-4	0.263	0.130	-0.133	-0.396	(-2.90)
5 (Buy)	0.202	0.002	-0.284	-0.486	(-4.12)

Panel D: 12 Months - 12 Months

	Industry Proportion Bought				
Firm Proportion Bought	1 (Sell)	2-4	5 (Buy)	Q5 -Q1	t-statistic
1 (Sell)	0.415	0.203	0.153	-0.262	(-1.81)
2-4	0.282	0.132	-0.030	-0.312	(-1.93)
5 (Buy)	0.203	-0.021	-0.297	-0.500	(-2.96)

Table 7: Retail Investor Industry and Stock Selection

This table decomposes the performance of retail investor trading into two components: industry selection and stock selection. Portfolios are formed on the basis of prior retail investor firm-level proportion bought. The return of the portfolio (total return) is the value-weighted average of the stocks return in that portfolio. The industry return is computed by substituting the return of the stock in the portfolio by the value-weighted return of the industry to which that stock returns. Stock return is defined as the difference between the total return and the industry return. Market-adjusted returns are the difference between the portfolio return and the value-weighted market return. Five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. The differences in return between quintile 5 and 1 is also reported, along with t- statistics in parentheses. The formation and holding period is 1 week in Panel A, 3 months in Panel B, 6 months in Panel C, and 12 months in Panel D.

Panel A: 1 Week – 1 Week

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	-0.326	-0.192	-0.134	-0.289	-0.153	-0.136
2	-0.239	-0.089	-0.150	-0.293	-0.131	-0.162
3	0.149	-0.054	0.203	0.123	-0.081	0.204
4	0.189	-0.015	0.204	0.201	0.012	0.189
5 (bought)	0.480	0.262	0.218	0.502	0.272	0.230
B-S (5-1)	0.806	0.454	0.352	0.791	0.425	0.366
	(6.49)	(3.47)	(2.39)	(6.21)	(3.18)	(2.76)

Panel B: 3 Months – 3 Months

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.426	0.301	0.125	0.440	0.323	0.117
2	0.229	0.153	0.076	0.203	0.129	0.074
3	0.119	0.029	0.090	0.020	-0.021	0.041
4	-0.062	-0.025	-0.037	-0.123	-0.012	-0.111
5 (bought)	-0.103	-0.006	-0.097	-0.150	0.021	-0.171
B-S (5-1)	-0.529	-0.307	-0.222	-0.590	-0.302	-0.288
	(-3.45)	(-2.12)	(-1.53)	(-3.89)	(-2.03)	(-1.73)

Panel C: 6 Months – 6 Months

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.486	0.302	0.184	0.502	0.248	0.254
2	0.186	0.199	-0.013	0.142	0.172	-0.030
3	-0.035	-0.002	-0.033	-0.065	0.029	-0.094
4	0.019	-0.015	0.034	0.002	0.071	-0.069
5 (bought)	-0.013	0.005	-0.018	-0.034	-0.091	0.057
B-S (5-1)	-0.499	-0.297	-0.202	-0.536	-0.339	-0.197
	(-2.98)	(-2.00)	(-1.47)	(-3.19)	(-2.10)	(-1.25)

Panel D: 1 Year – 1 Year

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.402	0.298	0.104	0.391	0.285	0.106
2	0.135	0.177	-0.042	0.119	0.159	-0.040
3	0.089	-0.002	0.091	-0.020	-0.021	0.001
4	-0.008	-0.015	0.007	-0.020	0.012	-0.032
5 (bought)	0.009	0.050	-0.041	-0.015	0.021	-0.002
B-S (5-1)	-0.393	-0.248	-0.145	-0.405	-0.264	-0.141
	(-2.09)	(-1.76)	(-1.07)	(-2.31)	(-1.81)	(-0.97)

Figure 1: **Cross-Sectional Correlation of Industry Proportion Bought**

Each week from January 4, 1983 to December 27, 2000 we compute retail investor (institutional) industry proportion bought. This figure reports the time-series average of the cross-sectional correlations between retail investor (institutional) industry proportions bought in week *t*, and week *t+x*. The x axis represents different horizons.